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REVIEW ARTICLE

A methodological framework for analysis of participatory mapping data in research, planning, and management

Nora Fagerholm[a], Christopher M. Raymond[b,c,d], Anton Stahl Olafsson[e], Gregory Brown[f,g], Tiina Rinne[h], Kamyar Hasanzadeh[h], Anna Broberg[i] and Marketta Kyttä[h]

[a]Department of Geography and Geology, University of Turku, Turku, Finland; [b]Helsinki Institute for Sustainability Science (HELSUS), University of Helsinki, Helsinki, Finland; [c]Ecosystems and Environment Research Program, Faculty of Biological and Environmental Sciences, University of Helsinki, Helsinki, Finland; [d]Department of Environmental Economics and Resource Management, Faculty of Agriculture and Forestry Sciences, University of Helsinki, Helsinki, Finland; [e]Department of Geosciences and Natural Resource Management, University of Copenhagen, Copenhagen, Denmark; [f]Natural Resources and Environmental Sciences Department, California Polytechnic State University, San Luis Obispo, United States; [g]School of Earth and Environmental Sciences, University of Queensland, Brisbane, Australia; [h]Department of Built Environment, Aalto University, Helsinki, Finland; [i]Mapita Ltd, Helsinki, Finland

ABSTRACT

Today, various methods are applied to analyze the data collected through participatory mapping, including public participation GIS (PPGIS), participatory GIS (PGIS), and collecting volunteered geographic information (VGI). However, these methods lack an organized framework to describe and guide their systematic applications. Majority of the published articles on participatory mapping apply a specific subset of analyses that fails to situate the methods within a broader, more holistic context of research and practice. Based on the expert workshops and a literature review, we synthesized the existing analysis methods applied to the data collected through participatory mapping approaches. In this article, we present a framework of methods categorized into three phases: *Explore*, *Explain*, and *Predict/Model*. Identified analysis methods have been highlighted with empirical examples. The article particularly focuses on the increasing applications of online PPGIS and web-based mapping surveys for data collection. We aim to guide both novice and experienced practitioners in the field of participatory mapping. In addition to providing a holistic framework for understanding data analysis possibilities, we also discuss potential directions for future developments in analysis of participatory mapping data.

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Online participatory mapping; Public participation GIS (PPGIS); participatory GIS (PGIS)

1. Introduction

The last two decades of the Western and non-Western world have witnessed increasing interest in the participatory mapping approaches, applied in a variety of fields of research and practice (Brown *et al*. 2020). Various terms have been used to describe these approaches, the most prominent being public participation geographical information systems (PPGIS), participatory GIS (PGIS), and volunteered geographic

CONTACT Nora Fagerholm ncfage@utu.fi

information (VGI) (Verplanke *et al*. 2016). Today, participatory mapping approach has roused the interest of academics and a wide user community. This is evident from the increasing number of academic publications, conferences, workshops, and journal special issues pertaining to this field (see, e.g., Brown and Fagerholm 2015, Mukherjee 2015, Brown and Kyttä 2018). Furthermore, participatory mapping now has an international professional society, comprising scholars and practitioners, invested in its integrity, accuracy, data collection, and the equitable distribution of knowledge (International Society for Participatory Mapping 2020).

As noted by Brown and Kyttä (2014), PPGIS, PGIS, and VGI are related spatial terms with sufficient differences to warrant nuanced descriptions. PPGIS approaches promote the use of GIS and modern communication technologies to engage the general public and stakeholders to carry out informed participatory planning and decision-making, particularly in the context of urban and regional development (Sieber 2006). The term PGIS emphasizes empowerment and can be traced to the merger of Participatory Learning and Action methods with geographic information technologies in the Global South (Rambaldi *et al*. 2006). The term VGI, introduced by Goodchild (2007), describes a phenomenon where citizens voluntarily create, collect, validate, analyze, and disseminate geographic information. Collecting VGI is based more on contribution and communication of information, than on participation (Verplanke *et al*. 2016). Collecting VGI conceptually resembles PPGIS approaches owing to the use of typical online tools to harness spatial information (Hall *et al*. 2010). In this paper, we have adopted the use of the term PPGIS, although some of the empirical work we discuss could be described as PGIS or collecting VGI.

PPGIS approaches seek to understand location-specific human values, perceptions, behavior, and preferences for future land use and development. Methods for analyzing spatially referenced data, collated using PPGIS, have been developed in diverse directions. Among others, these include analyzing sampling effects and response bias (e.g., Brown *et al*. 2014a, Brown 2017, Munro *et al*. 2017), representing diversity, abundance, or rarity of value points (Bryan *et al*. 2011); examining the level of overlap in values across different stakeholder groups (Muñoz *et al*. 2019), identifying the potential for value or preference conflicts (e.g., Brown and Raymond 2014, Kahila-Tani *et al*. 2016, Plieninger *et al*. 2018, Wolf *et al*. 2018); assessing environmental justice issues (Raymond *et al*. 2016); and bridging the divide between experts and the public (Whitehead *et al*. 2014, Zolkafli *et al*. 2017a). Despite the plethora of analysis methods available to explore, explain, and predict spatial attributes collated using PPGIS, most published articles apply a specific subset of analyses that fails to situate the methods within a broader, more holistic context of research and practice. Hence, the field currently lacks a methodological framework, making it essential to synthesize the various existing analysis methods to guide their processes and applications.

In this paper, we aim to produce a systematic framework of PPGIS data analysis methods supported by examples from published empirical studies. Our focus is mainly limited to the online PPGIS approaches, particularly the web-based mapping survey, the most common administrative technique for PPGIS data collection (Brown and Kyttä 2014). In order to provide context for our proposed framework, we first discuss spatial and non-spatial attributes in PPGIS surveys and implications of the combination of these on the quality of the PPGIS data produced and the methods for data analyses. This is followed by presentation of our views on the different phases in PPGIS data analysis (*Explore, Explain, Predict/Model*) and identifying the methods, purposes, and analytical approaches, highlighting each with example studies and application domains, based on expert workshops and extensive literature review of peer-reviewed articles. Finally, we recommend potential future development directions for PPGIS analysis methods. The methods of analyses described herein are relevant to different applications including conservation and natural resource planning and urban and regional development. We aim to guide researchers and practitioners, both new and experienced, interested in PPGIS approaches, to address academic, or applied questions relevant to exploration, explanation, and prediction.

2. Methods

To draft and develop the methodological framework, the authors conducted a one-day expert workshop in August 2018, at the Aalto University in Helsinki, Finland. This was the first of the two workshops held at Aalto University where we discussed possible ways to categorize analysis methods. The second workshop held in October 2018 saw further refinements to the framework along with drafting of the manuscript contents and planning the literature review. Moreover, in January 2019 we searched for peer-reviewed articles using the Scopus electronic database (document search: title, abstract, keywords, and publication year 2004 to 2019) to gather examples of empirical studies that applied a broad range of data analysis methods, and contained the keywords: participatory GIS, participatory mapping, public participation GIS, PPGIS, SoftGIS, and geo-questionnaire. We identified 279 such published papers. We reviewed these articles to describe the applied analysis methods. Based on expert judgment, we also included several published papers that did not appear in the search results. In the third and final workshop held in December 2018 at the University of Turku in Turku, Finland, we critically reflected on the manuscript content, results of the literature review, and discussed future directions in the field of participatory mapping.

Although the article focuses on the online PPGIS approaches, we acknowledge that the presented methods can also be applied to analyze data collected through analog approaches (e.g. interviews, workshops, and mail surveys). Hence, we have included some offline PPGIS approaches to cover the range of methods and highlighted important examples where specific methods were applied for the first time. Online PPGIS surveys also include data collected from individuals, which is then aggregated to the scale of the survey population (Brown *et al*. 2015a), as opposed to deliberative valuation where the emphasis is on group negotiation and compromise, including the mapping of shared and social values (Raymond *et al*. 2014, Kenter 2016).

3. Data collection through PPGIS surveys and data quality

PPGIS data analysis methods are constrained by data quality. The PPGIS process includes the phases of survey/website design, participant recruitment, and data collection, followed by data analysis. All phases are important and should be carefully prepared. Survey design identifies the spatial and non-spatial information to be collected which influences the user experience (Swobodzinski and Jankowski 2014, Poplin 2015, Gottwald *et al*.

2016), participation rates, and ultimately, the quality of spatial data and the possibilities of analysis offered.

There exists several recruitment methods for online PPGIS surveys, ranging from random samples drawn from a national population or household registers (Hausner *et al*. 2015, Kyttä *et al*. 2015, Laatikainen *et al*. 2019), purposive sampling (Garcia-Martin *et al*. 2017), and crowdsourced/volunteer sampling through traditional or social media (Kahila-Tani *et al*. 2016, Rall *et al*. 2017) to using internet survey panels (Brown *et al*. 2012, Munro *et al*. 2017). To improve the quality of spatial data generated, other participant recruitment strategies, such as collecting data in schools when studying children and young people (Kyttä *et al*. 2012, 2018b) or applying facilitated mapping processes where survey respondent receives assistance (Zolkafli *et al*. 2017b, Fagerholm *et al*. 2019a), can also be used. In a recent review, Kahila-Tani *et al*. (2019) found that the data collection strategy impacts sample representativeness; random sampling seems to promote good representativeness while crowdsourced/volunteer sampling poses a challenge to reaching a balanced respondent profile.

The quality of PPGIS data also depends on many other factors including mapping efforts, accuracy, and precision, type of spatial data collected, and data usability in terms of how it fits the purpose (Brown and Kyttä 2014, Brown and Fagerholm 2015, Jankowski *et al*. 2016, Kahila-Tani *et al*. 2019). There are always practical limitations to the time and efforts exerted by the respondents in a survey. A meta-analysis shows that household sampling groups always dedicate more mapping efforts as compared to volunteer groups (Brown 2017). Cognitive challenges may vary depending on the type of data being collected through mapping, that is, objective or subjective. For instance, place-related activities and experiences seem to be cognitively less challenging to map as compared to place-related values and concepts such as ecosystem services (Brown 2017).

PPGIS data collection through online surveys are often self-administered, where individuals map spatial attributes of importance without outside assistance. These attributes can relate to mapping of either points, lines, or polygons, with points being the most commonly used and simple geographic feature in PPGIS (Brown and Fagerholm 2015). The mapped *spatial PPGIS data* attributes can, for example, signify a respondent's:

(1) Spatial values, perceptions, or attitudes, e.g., landscape values (Brown and Raymond 2007), perceived environmental quality factors (Kyttä *et al*. 2013), and ecosystem service benefits (Ridding *et al*. 2018, Fagerholm *et al*. 2019a), in addition to perceived problems or unpleasant experiences (Raymond *et al*. 2016);
(2) Spatial behavior patterns, everyday practices, and activities, e.g., daily mobility patterns, and routes travelled (Laatikainen *et al*. 2017, Kajosaari *et al*. 2019), places visited (Sarjala *et al*. 2015), and their temporal characters, e.g., seasonality, length, or frequency of visitation (Bijker and Sijtsma 2017);
(3) Spatially defined future preferences or visions, e.g. development preferences (Brown 2006, Raymond and Brown 2007, Jankowski *et al*. 2016, Kahila-Tani *et al*. 2016, Engen *et al*. 2018); and
(4) Preferred place features referred to as 'geographic citizen science' (Haklay 2013), e.g., mapping road/trail networks (e.g., OpenStreetMap) and wildlife observations (Brown *et al*. 2018a). These spatial data can be used to augment and validate authoritative data.

In addition to mapping the spatial attributes, open or structured follow-up questions can be asked to describe the mapped attributes. These follow-up questions often appear in a pop-up window with relation to the mapped places in the survey. Videos, photos, and recorded stories can also be captured for the mapped places (e.g., Kahila-Tani *et al*. 2018).

Along with their focus on mapping, spatial surveys often include *non-spatial PPGIS data* collected through traditional open or structured questions (Figure 1). Such non-spatial data may include, but are not limited to, questions addressing:

(1) Socio-economic-demographic characteristics, e.g. age, gender, education, and income levels;
(2) Personal general values, attitudes, and preferences, e.g., lifestyle preferences, environmental worldviews, beliefs, and norms;
(3) Personal motivation and behavioral intentions, e.g., personal goals, and likelihood to engage in special behavior;
(4) Personal well-being, happiness, health, and satisfaction, e.g., perceived health, perceived quality of life, and neighborhood satisfaction; and
(5) Level of trust in planning and decision-making processes for land use.

An important trade-off in survey design relates to the abundance of spatial data versus descriptive depth of mapped places. When targeting a considerable number of mapped places by each survey respondent, the respondents are likely reluctant to spend significant time to describe the mapped places in-depth. Similarly, when aiming for

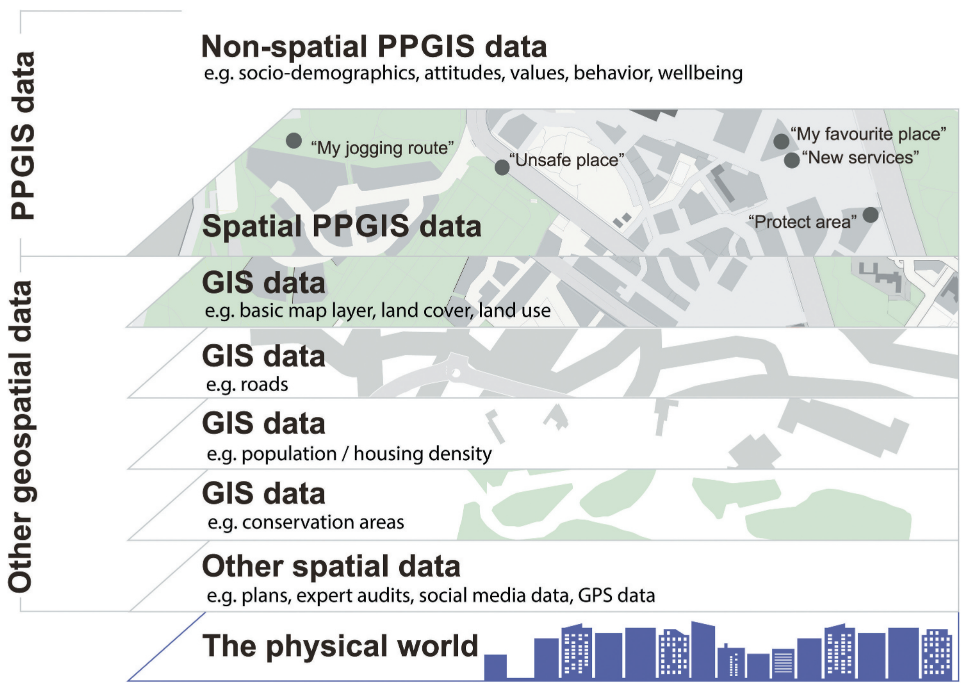

Figure 1. PPGIS survey data structure with mapped spatial and non-spatial data, and links to other geospatial data.

detailed descriptions of numerous-mapped places, it is likely that the respondent's efforts may not be sufficient. Hence, in terms of survey design, it is crucial to balance the quantity of mapped spatial data with the corresponding descriptions; in each case, it is important to critically reflect on the most essential information for the purpose of the study. Hence, data quality can be controlled when designing the survey and this affects analysis possibilities for the data.

4. Other geospatial data in PPGIS data analysis

PPGIS datasets are often combined with other geospatial data during analysis (Figure 1). Typical examples include land cover, land use, and road network data. CORINE land cover is an openly accessible European example of a land cover and land use dataset (https://land.copernicus.eu/pan-european/corine-land-cover/clc-2012). Although, road network datasets, comprising national road datasets, are available, the use of Open Street Map (www.openstreetmap.org), an open geospatial road dataset produced by a community of mappers, has become common. Furthermore, versatile geographically referenced statistical data pertaining to population, species, city plans, population and housing density, conservation areas, zoned land units, real estates, buildings, and service and company locations can be used concurrently with PPGIS data. Participatory mapping also provides an opportunity to conduct ex-post planning evaluation, to obtain feedback from inhabitants regarding the performance of neighborhood, city, or regional level planning solutions once they are accomplished. PPGIS datasets can therefore be analyzed along with urban or spatial plans (Kyttä *et al*. 2014). To understand the actual realization of these plans, this analysis can be complemented with expert audit data of the physical environment (2018a) and virtual audits, now possible with the help of Google Street View (Rzotkiewicz *et al*. 2018). Additional spatially referenced datasets include social media data (Toivonen *et al*. 2019) and data produced through GPS tracking (Wolf *et al*. 2015).

5. Analysis of PPGIS data: a framework with three phases

Analysis methods applied to PPGIS data can be represented as a framework of three analytical phases: *Explore*, *Explain*, and *Predict/Model*. These phases graduate from basic to advanced. The three phases of the framework relate to different types of knowledge claims, as an output of PPGIS data analysis. The *Explore* phase defines the exploratory and descriptive character of the analysis method (Figure 2). Such methods are generally termed as exploratory spatial data analysis (De Smith *et al*. 2020). The analysis does not require high expertise and can be done by non-academics such as planners and stakeholders. The *Explain* phase aims to understand the relationship between PPGIS data and multiple other geospatial data sources. This phase demands expertise in analytical methods. The *Predict/Model* phase intends to generalize mapped attributes to other places and contexts, and to understand future realities. This phase typically requires advanced expertise to perform analyses that integrate multiple data sources to predict and model PPGIS data.

The presented framework suggests a logical progression in data analysis. However, in reality, analysis often proceeds iteratively going back and forth between the different

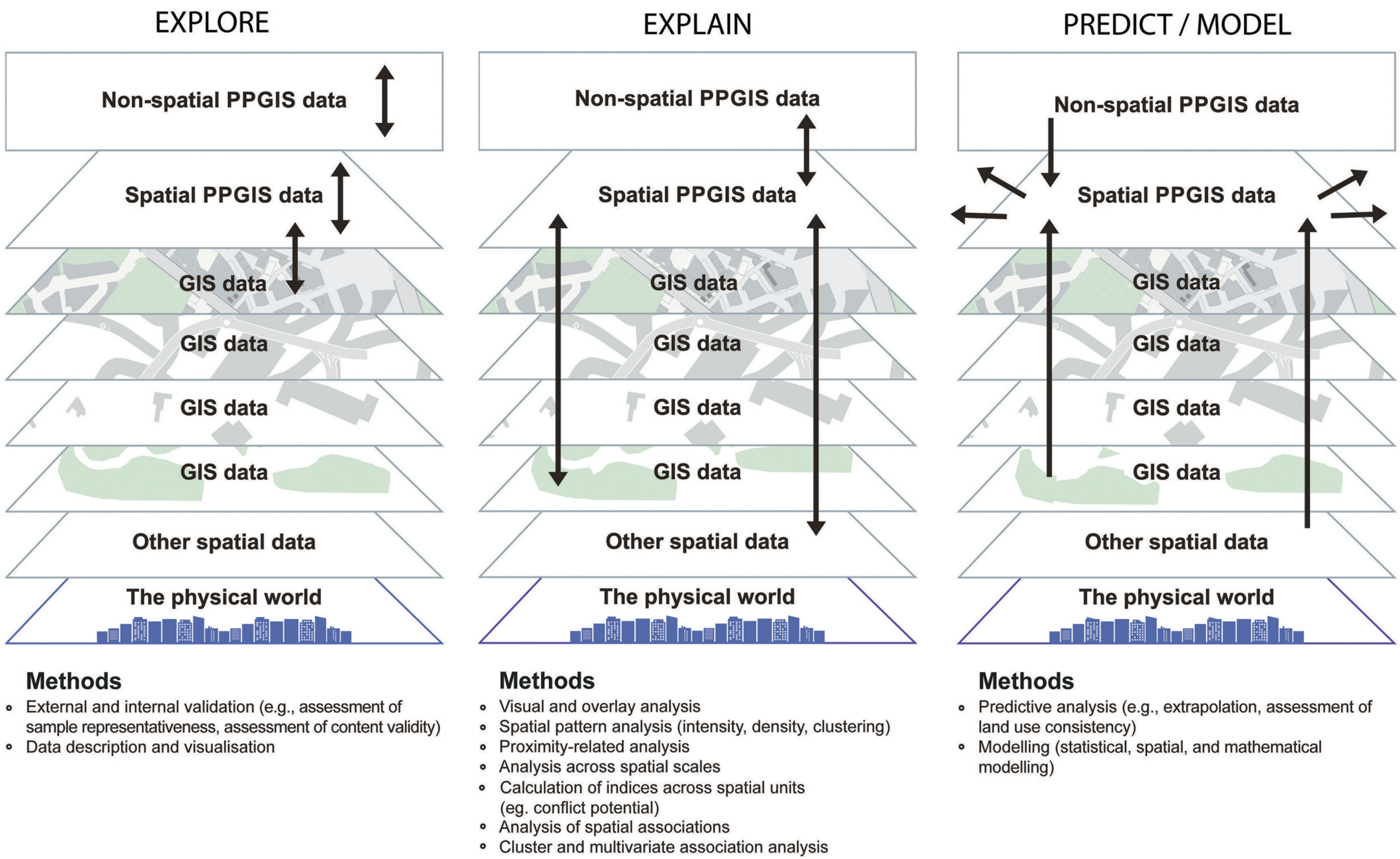

Figure 2. Three analysis phases *Explore, Explain*, and *Predict/Model* for data gathered through PPGIS approaches and links in each phase between PPGIS data and other geospatial data.

Table 1. PPGIS analysis methods, purposes, and example tools in *Explore* phase. Goals in *Explore* phase include assessment of spatial data quality and uncertainty, data exploration through simple univariate statistics, and visualization of spatial patterns.

Method	Purpose	Example tools/approaches	Examples of references
External and internal validation			
External validation through assessment of sample representativeness and application of mapping methods to other social and geographic contexts	Assessing PPGIS spatial data quality (external)	Assessment of sample representativeness e.g. comparison of random vs. volunteered samples, analysis of different sample cohorts, application of mapping methods and data typologies in multiple geographic locations to compare the results	Brown *et al.* (2014a), Lechner *et al.* (2014), Brown (2017), Brown and Hausner (2017), Munro *et al.* (2017)
Internal validation	Assessing PPGIS spatial data quality (internal)	Assessment of content validity, criterion validity, and construct validity, identifying extreme mappers as outliers, measuring positional accuracy, correctness and completeness validity, testing spatial autocorrelation (i.e. global clustering): nearest neighbor index and Moran's I	Bryan *et al.* (2011), Lechner *et al.* (2014), van Riper and Kyle (2014), Brown *et al.* (2015a), Jankowski *et al.* (2016), Rohrbach *et al.* (2016), Pietilä and Fagerholm (2016, Brown *et al.* (2017a), Garcia-Martin *et al.* (2017)
Descriptive and visual analysis			
Data description	Quantitatively and qualitatively explore data	Frequencies and simple descriptive statistics (univariate analysis)	*Applicable to most cases*
Data visualization	Visually explore spatial patterns in data	Thematic maps, varying symbolization, charts	Ramirez-Gomez *et al.* (2013), Samuelsson *et al.* (2018), Kajosaari *et al.* (2019)

phases. Moreover, it is not necessary to perform data analysis in all phases. For example, data analysis can simply focus on the first phase, *Explore*. Each phase of our framework and its related methods have been presented in the following sections. Since earlier literature have not given due justice to spatial PPGIS data analysis options, our paper specially focuses on these.

5.1. *Explore*

The first analytical phase, *Explore*, involves descriptive and univariate analysis of PPGIS data and generation of visual outputs. Spatial patterns are identified for one attribute at a time (univariate analysis) and compared across available attributes. Though the analyses in *Explore* phase focus on spatial and non-spatial PPGIS data, it incorporates other geospatial data merely as cartographic background information. The analyses are accomplished with basic GIS software or with the help of the interactive analysis tools provided by some online PPGIS services. An important part of *Explore* phase is the assessment of spatial data quality through validation. Before the data enter the exploration phase, PPGIS data need to be cleaned by detecting, correcting, or removing inaccurate spatial records, and organized for subsequent data analysis. Such data manipulation may include value (re)classification, data (re)ordering, data queries, and removal of outliers.

5.1.1. External and internal validation

External and internal assessment of spatial data quality and uncertainty is important (Lechner *et al*. 2014). External validation addresses assessment of sampling strategy, size, and representativeness (i.e., a comparison of sample characteristics within a wider population) (Table 1). Exploration can also include comparison of different sampling groups, e.g., comparison between random versus volunteer samples (Brown *et al*. 2014a) or different cohorts in the sample to assess sample representativeness (Munro *et al*. 2017). Testing whether the spatial results can be generalized to other locations, people, and situations is challenging because PPGIS studies are case studies with a unique mix of place-based contextual variables. External validity can be indirectly assessed by performing meta-analysis with multiple PPGIS studies to examine which spatial variables appear valid across different place settings. For instance, Brown and Hausner (2017) analyzed the distribution of mapped cultural ecosystem values in coastal areas of five countries and found that the mapped values were significantly more abundant in all coastal zones, regardless of ecosystem value category, country, population, or dominant land use.

Internal data validation involves assessing validity of content, criterion, and construct (see Brown *et al*. (2017a) for application of data validity concepts to quantitative and qualitative PPGIS data). Measurement of positional accuracy, correctness, and completeness validity (Brown *et al*. 2015a, Jankowski *et al*. 2016, Rohrbach *et al*. 2016) is also a part of internal data validation. To explore global clustering, the data are commonly tested for spatial autocorrelation through nearest neighbor index (e.g., van Riper and Kyle 2014, Pietilä and Fagerholm 2016) and Moran's I (e.g., Garcia-Martin *et al*. 2017). These descriptive statistical methods help to understand spatial distribution of the mapped data.

5.1.2. Descriptive and visual analysis

Simple univariate descriptive analysis is applied in the *Explore* phase to study PPGIS data qualitatively and quantitatively (Table 1). Visual outputs, in form of thematic maps and charts, are often generated to examine the spatial patterns (e.g., Ramirez-Gomez *et al*. 2013, Samuelsson *et al*. 2018, 261, Kajosaari *et al*. 2019)

5.2. Explain

The second phase, that is, *Explain*, aims to look more closely at observations than the *Explore* phase, in order to explain observations by further analysis. A wide variety of PPGIS data analysis methods are categorized within this phase. The *Explain* phase essentially combines spatial and non-spatial PPGIS data with other geospatial data. Thus, several methods including inferential and multivariate statistics are used in this phase; it also involves the use of various statistical software along with GIS software.

Table 2. PPGIS analysis methods, purposes, example tools and application domains in *Explain* phase. The goals in *Explain* phase include looking more closely at observations from *Explore* phase and finding explanation for the observations by further analysis of the data, in relation to other geospatial data.

Method	Purpose	Example tools/approaches	PPGIS application domains	Example references
Visual and overlay analysis				
Visual analysis	Visually analyze spatial patterns in data using multiple datasets	Multiple simultaneous views, overlaid maps	*Applicable to all domains*	Kyttä *et al.* (2013), Laatikainen *et al.* (2017), Brown *et al.* (2018b)
Overlay analysis	Analyze overlap among mapped features or to other GIS data	Overlay analysis	Conservation planning, ecosystem service assessment, landscape management, marine and coastal spatial planning, natural resource management, urban planning	Raymond *et al.* (2009), Whitehead *et al.* (2014), Fagerholm *et al.* (2016), Kyttä *et al.* 2018a), Rall *et al.* (2019)
Spatial pattern analysis				
Spatial pattern analysis (intensity/ density)	Analyze intensity/density of features as surface	Point density, Kernel density estimation	Ecosystem service assessment, land use planning, landscape management, marine and coastal spatial planning, protected area management, tourism management, urban planning	Alessa *et al.* (2008), Sherrouse *et al.* (2011), Pocewicz and Nielsen-Pincus (2013), Hausner *et al.* (2015), Fagerholm *et al.* (2016), Munro *et al.* (2017), Rall *et al.* (2017), Kantola *et al.* (2018), Pánek (2018)
Spatial pattern analysis (clustering)	Analyze the level of clustering/dispersion of mapped features	Local methods for statistically significant spatial clustering/dispersion (e.g. hots spot identification through Getis-Ord Gi*, cluster identification through Nearest Neighbour Analysis, distance band of the mean distance identification and aggregation to polygons; cluster identification through Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm)	Conservation planning, ecosystem service assessment, land use planning, tourism management, urban planning	Brown and Raymond (2014), Karimi *et al.* (2015), Raymond *et al.* (2016), Bagstad *et al.* (2017), Laatikainen *et al.* (2017), Brown and Glanz (2018), Muñoz *et al.* (2019)
Proximity-related analysis				
Proximity analysis	Analyze the proximity of features to each other and/or to features from other GIS data	Distance analysis, buffer analysis, proximity neighborhood, home range analysis	Ecosystem service assessment, landscape management, land use planning, natural resource management, urban planning	Brown (2013), Brown *et al.* (2015b), Kyttä *et al.* (2015), Brown and Hausner (2017), Hasanzadeh *et al.* (2017), Laatikainen *et al.* (2017), Brown and Glanz (2018), Brown *et al.* (2018b), Ridding *et al.* (2018), Kajosaari *et al.* (2019)
Viewshed analysis	Analyze viewshed from mapped features	Calculate viewshed based on topographic model (Digital Elevation Model)	Ecosystem service assessment, landscape management	Garcia-Martin *et al.* (2017), Ridding *et al.* (2018)

(*Continued*)

Table 2. (Continued).

Method	Purpose	Example tools/approaches	PPGIS application domains	Example references
Analysis across spatial scales				
Analysis across spatial scales	Analyze PPGIS data across different spatial scales	Defined scales based on administrative boundaries or Euclidian distance	Ecosystem service assessment, landscape management, protected area management, tourism management, urban planning	Pietilä and Fagerholm (2016), Bijker and Sijtsma (2017), Hausner *et al.* (2015), Ives *et al.* (2018), Ridding *et al.* (2018)
Calculation of indices across spatial units				
Spatial indices i.e. social landscape metrics	Quantify distribution of mapped features across spatial units (e.g. land use/management/cell units)	Metrics including, e.g. diversity, abundance, dominance, rarity, complementarity, centricity	Ecosystem service assessment, landscape management, natural resource management, protected area management, tourism management, urban planning	Bryan *et al.* (2010), Brown and Reed (2012a), Broberg *et al.* (2013), Pietilä and Fagerholm (2016), Raymond *et al.* (2016), Hasanzadeh (2019)
Conflict potential identification	Identify potential tensions between mapped attributes across spatial units	Conflict potential indices (e.g. preference score, weighted preference score, preference and value score, value compatibility score	Conservation planning, ecosystem service assessment, landscape management, land use planning, natural resource management	Brown and Raymond (2014), Lechner *et al.* (2015), Brown *et al.* (2017b), Karimi and Brown (2017), Brown *et al.* (2018c), Plieninger *et al.* (2018)
Suitability and consistency analysis	Identify suitability for a specific land use or consistency with a proposed land use across spatial units	Suitability analysis as overlay through multiple criteria; consistency analysis	Land use planning, natural resource management, protected area management	Reed and Brown (2003), Brown and Reed (2012b), Brown *et al.* (2018c)
Analysis of spatial associations				
Spatial association	Analyze relationship between mapped features and physical/administrative land properties or between pairs of mapped features	Cross tabulation with chi-square statistics, standardized residuals and Z scores), Spearman's rank correlations, Phi correlation coefficient, Jaccard coefficient, Pearson's product moment correlations	Climate change planning, ecosystem service assessment, landscape management, land use planning, marine and coastal spatial planning, urban planning	Zhu *et al.* (2010), Raymond and Brown (2011), Brown and Brabyn (2012a), Plieninger *et al.* (2013), Brown and Hausner (2017), Garcia-Martin *et al.* (2017), Rall *et al.* (2017), Fagerholm *et al.* (2019a)
Cluster and multivariate association analysis				
Data clustering	Create clusters of mapped features and/or other GIS data (e.g. land use)	Statistical clustering (e.g. multiple correspondence analysis, hierarchical cluster analysis, principal component analysis)	Ecosystem service assessment, landscape management, land use planning, urban planning	Plieninger *et al.* (2013), Hausner *et al.* (2015), Brown *et al.* (2015c), Rall *et al.* (2017)
Association analysis	Find relationships between mapped features, respondent groups and/or attributes from other GIS data	Correlation, regression models, redundancy analysis; generalized linear models, generalized linear mixed models, structural equation modeling	Ecosystem service assessment, landscape management, protected area management, urban planning	Bryan *et al.* (2011), Kyttä *et al.* (2012), Plieninger *et al.* (2013), Kyttä *et al.* (2015), Fagerholm *et al.* (2016), Pietilä and Fagerholm (2016), Garcia-Martin *et al.* (2017), Pánek *et al.* (2017), Rall *et al.* (2017), Engen *et al.* (2018), Ridding *et al.* (2018), Fagerholm *et al.* (2019a), Kajosaari *et al.* (2019), Laatikainen *et al.* (2019)

5.2.1. Visual and overlay analysis

Visualization of spatial patterns is typically part of *Explain* phase, but as a contrast to *Explore* phase, visual analysis includes generation of multiple simultaneous views or overlay maps (e.g. Kyttä *et al.* 2013, Laatikainen *et al.* 2017, Brown *et al.* 2018b) (Table 2). Overlay analysis, where multiple inputs are overlapped to generate new information, is common for viewing different mapped attributes or studying their relation to other geospatial data such as city plans, land use or ecologically valuable areas (e.g., Whitehead *et al.* 2014, 2018a, Rall *et al.* 2019).

5.2.2. Spatial pattern analysis

A broadly applied method in multiple studies to analyze spatial patterns of PPGIS data is to produce a spatially continuous intensity/density surface of mapped attributes through Kernel density estimation (Silverman 1986) (e.g., Alessa *et al.* 2008, Sherrouse *et al.* 2011, Pocewicz and Nielsen-Pincus 2013, Fagerholm *et al.* 2016) (Table 2). A simpler version of intensity surface can be calculated through point density analysis (Hausner *et al.* 2015, Kantola *et al.* 2018). Alessa *et al.* (2008) investigated spatial interpolation methods (e.g., kriging) for intensity surface mapping, but concluded that this method appears appropriate when the interpolated variable has a continuous spatial coverage across an area (e.g., air temperature).

Clustering or dispersion of mapped attributes can be approached through methods developed for identifying statistically significant hot and cold spots, such as Getis-Ord Gi* statistics (Getis and Ord 1992). These methods have been applied extensively by Brown and Raymond (2014), Karimi *et al.* (2015), and Bagstad *et al.* (2017). Cluster identification through average nearest neighbor distance analysis has also been applied to create boundaries for clusters of mapped attributes (Raymond *et al.* 2016). Furthermore, Laatikainen *et al.* (2017) identified a corresponding distance band of the mean distance of the mapped points, based on which, points were aggregated to polygons to capture elongated clusters along the shoreline. Muñoz *et al.* (2019) implemented a Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm (Ester *et al.* 1996) to find areas with highest density of mapped place values.

5.2.3. Proximity-related analysis

There are various types of analysis available for exploring the proximity among the attributes in mapped data or in relation to other GIS data (Table 2). Distance of mapped attributes from domicile can be useful to explain variation in spatial patterns of mapped attributes (Brown *et al.* 2018b). Circular buffers at specified distances around home or mapped places allow for calculation of the amount of different land uses and other GIS variables describing urban structure (Kyttä *et al.* 2015, Laatikainen *et al.* 2017) or landscape characteristics (Ridding *et al.* 2018) within the neighborhood of a mapped place. Brown (2013) applied circular buffer analysis to multiple radii to analyze the cumulative proportion of mapped forest values located within the neighborhood of mapped forest use preferences. Similarly, Brown and Hausner (2017) examined the distribution of mapped ecosystem values in coastal and non-coastal zones using multiple distance bands from the coastline. Circular buffers are also applied as the first step to identify home range, a concept common in ecology (Burt 1943), to spatially identify individual place attachment or activity space in PPGIS data. In addition, minimum convex polygon around mapped attributes has been suggested as an operational model to define home ranges (Brown *et al*. 2015b, Hasanzadeh *et al*. 2017).

Proximity analysis is also used in viewshed analysis to calculate the range of visible territory in all directions at specified distances from a mapped attribute based on topography, using elevation values from Digital Elevation Models. The viewsheds of specific landscape values may be compared to the average viewshed for that attribute in the data (Garcia-Martin *et al*. 2017) or may be used to calculate the proportion of landscape characteristics variables derived from various GIS data within the viewshed of mapped outdoor locations (Ridding *et al*. 2018).

5.2.4. Analysis across spatial scales

Interactions of mapped locations with the surrounding landscape at different spatial scales (Table 2) were examined by Pietilä and Fagerholm (2016), who analyzed mapped tourism impacts at destination, park zone, and site scale in the context of a national park and by Bijker and Sijtsma (2017), who analyzed important natural places on local, regional, national, and global scales. Moreover, Ridding *et al*. (2018) calculated landscape characteristic variables at different scales defined by 500 m and 5 km buffers around the mapped locations, whereas Ives *et al*. (2018) compared landscape values at suburb and municipality scales using metrics of value abundance and diversity.

5.2.5. Calculation of indices across spatial units

Distribution of mapped attributes can also be analyzed across spatial units, such as land-use class, land management type, or grid cells using spatial indices (Table 2). Such indices, developed initially in landscape ecology (McGarigal and Marks 1995), have been modified for the purposes of PPGIS data and include, e.g. richness, diversity, abundance, dominance, rarity, and complementarity (Bryan *et al*. 2010, Brown and Reed 2012a). Brown and Reed (2012a) presented a detailed elaboration of these 'social landscape metrics' and distinctions between boundary and inductive metrics. These spatial indices have been widely applied and further developed in PPGIS research in various application domains (Broberg *et al*. 2013, Hausner *et al*. 2015, Hasanzadeh 2019).

One of the specific fields of interest to explain potential tensions between mapped place values and land-use preferences is the identification of conflict potential based on PPGIS data. Brown and Raymond (2014, Figure 1), proposed a conceptual model of land-use conflict potential as a function of the level of agreement on land-use preferences and place importance. This conceptualization yielded sampling grid-based methods for calculation of conflict indices using weighted and unweighted preferences, place values, and value compatibility scores. Application of these indices has been exemplified in practice, for example, by Brown and Raymond (2014) for residential and industrial development, Brown *et al*. (2017b) in natural resource management, and Plieninger *et al*. (2018) for land – and seascape values and development preferences. In addition, Karimi and Brown (2017) present an assessment of the different methods for conflict identification. Furthermore, Lechner *et al*. (2015) augmented the conflict identification approach to assess ecological connectivity.

Suitability analysis is another commonly used spatial analysis in land-use planning, wherein areas that are suitable for a specific land use are identified based on a set of decision criteria (see, e.g., Malczewski 2004). Suitability maps based on criteria (e.g., elevation, slope) are generated to provide individual data layers that are overlaid to identify areas of spatial intersection that can satisfy multiple criteria. Traditional suitability analysis has often relied on biophysical landscape features, but PPGIS data layers can be used to identify relevant social criteria, such as landscape values, to include in the analysis (Reed and Brown 2003, Brown and Reed 2012b). Consistency analysis is related to suitability analysis and seeks to identify the significant association of PPGIS mapped attribute's distribution (e.g., land-use preferences) with the current or proposed land uses (e.g., through zoning); it also assesses if the mapped attributes appear logically in accordance with the land use (Brown *et al*. 2018c). The consistency of PPGIS data with current or proposed land use can be interpreted with chi-square residual analysis, where spatial data are collected as frequencies.

5.2.6. Analysis of spatial associations

Spatial associations can be identified based on the relationships between mapped PPGIS attributes and physical or administrative land properties. These associations can be analyzed by tabulating the frequencies of mapped attributes within land units (cross tabulation) and calculating chi-square statistics and standardized residuals to examine the statistical association (Brown and Brabyn 2012a) (Table 2). In addition, calculation of Z scores reveals the statistically significant under – or over-representation of attributes in a given land unit as presented, for example, by Brown *et al*. (2015b), Brown and Hausner (2017) and Fagerholm *et al*. (2019a). Spearman's rank correlation analysis has been applied for the identification of spatial associations between pairs of mapped attributes such as ecosystem services or landscape values (e.g., Plieninger *et al*. 2013, Garcia-Martin *et al*. 2017). The spatial overlap between different-mapped attributes has been quantitatively measured using the phi correlation coefficient (Zhu *et al*. 2010, Rall *et al*. 2017), the Jaccard coefficient, and the Pearson's product moment correlations (Raymond and Brown 2011).

5.2.7. Cluster and multivariate association analysis

Creation of statistically significant clusters of mapped attributes, respondent groups, and/or other GIS data has been performed to identify bundles of perceived ecosystem services (i.e., sets of mapped ecosystem services that repeatedly appear together (Raudsepp-Hearne *et al*. 2010). Methods such as multiple correspondence analysis, hierarchical cluster analysis and principal component analysis have been used collectively to identify clusters/bundles of perceived ecosystem services in grid cells or land cover units (e.g., Plieninger *et al*. 2013, Rall *et al*. 2017).

Several methods identifying statistical associations have been applied to the PPGIS data to find associations between mapped attributes, respondent groups and/or attributes from other GIS data. At a preliminary level, Spearman's correlation is useful to analyze relationships between spatial and non-spatial PPGIS data or other GIS data; for example, to explore the association between spatially explicit social values and ecological values (Bryan *et al*. 2011), the perceived impacts of tourism and visitor satisfaction (Pietilä and Fagerholm 2016), cognition of fearful places in the urban environment, and presence of day/night (Pánek *et al*. 2017), and to understand the general importance of mapped ecosystem services and their place-specific importance (Rall *et al*. 2017).

At a more advanced level, regression models are the prominent multivariate modeling methods to analyze associations. Logistic regression models have been used to assess, for example, the connections between urban structure, children's behavioral patterns, and environmental experiences, and health measures (Kyttä *et al*. 2013), the adjusted odds of walking a high share of estimated monthly trips and travel distance in an urban context (Kajosaari *et al*. 2019), landscape characteristics associated with outdoor places of personal importance for the delivery of cultural ecosystem services (Ridding *et al*. 2018), and whether communities favor, or oppose human activities in protected areas when controlling the landscape characteristics, accessibility, and demographics (Engen *et al*. 2018). Redundancy analysis, a multivariate analog of regression, has been applied to examine potential relations between mapped ecosystem services on different land covers, subjective well-being, and socio-demographic characteristics (Fagerholm *et al*. 2016). Generalized linear models have been used to examine possible relationships between the mapped ecosystem services with frequency of green space use, affinity, and general importance of each service (Rall *et al*. 2017). Generalized linear-mixed models have been applied to quantify the relationship between biophysical landscape characteristics and mapped ES benefits across 13 study sites that showed grouped structure and spatial autocorrelation (Fagerholm *et al*. 2019a). Structural equation models have been used to assess contextual variation and mediation of different factors in linking urban structural characteristics with health and well-being outcomes (Kyttä *et al*. 2015, Laatikainen *et al*. 2019).

5.3. Predict/Model

The final analysis phase, *Predict/Model*, aims to generalize and predict mapped attributes to other places and contexts (prediction) or produce a representation of a system to make inferences (model). Analysis methods in this phase require multiple data sources in addition to PPGIS data and involve multivariate modeling. Performing analysis in *Predict/Model* phase requires in-depth expertise in applying GIS and statistical software. The phase may also demand skills in computer coding.

5.3.1. Predictive analysis

In the absence of empirical PPGIS data, quantitative relationships with physical landscape variables can be used to extrapolate, i.e.value transfer, mapped PPGIS attributes spatially for wider regions or even at national scale (Table 3). Brown and Brabyn (2012b) extrapolated regional landscape values to a national scale using empirical relationships between physical landscape character and mapped PPGIS attributes. Brown *et al*. (2015c) and Brown *et al*. (2016) used the percent of mapped ecosystem values, spatially associated with land cover classes, as value transfer coefficients to assess the similarity between actual-mapped ecosystem values and value transfer spatial distributions.

For assessment of land use consistency, the quantitative relationship between existing land classifications and perceived landscape values has also been applied to build predictive discriminant functions to classify prospective lands for conservation purposes (Raymond and Brown 2006). Generated land classes can be mapped and overlaid with expert-derived classifications to estimate agreements in land use.

To identify and predict how conservation priorities change with the inclusion of PPGIS data, Whitehead *et al*. (2014) used the open-source spatial conservation prioritization software, Zonation (Moilanen 2007), to identify areas where there were synergies and/or conflicts between species distributions and social values derived from mapped data.

Table 3. PPGIS analysis methods, purposes, example tools and application domains in *Predict/Model* phase. Goals in *Predict/Model* phase include generalizing and predicting mapped attributes to other places and contexts (prediction) or producing a representation of a system to make inferences (model).

Method	Purpose	Example tools/ approaches	PPGIS application domains	Examples of references
Predictive analysis				
Extrapolation	Predict a mapped feature for location where there is no data available	Spatial value transfer through extrapolation	Ecosystem service assessment, landscape management, land use planning	Brown and Brabyn (2012b), Brown *et al*. (2015c), Brown *et al*. (2016)
Assessment of land use consistency	Predicting boundaries (polygons) of land use using a suite of mapped features	Discriminant analysis	Protected area management	Raymond and Brown (2006)
Heuristic and approximate optimization methods for spatial prioritization	Identify conservation priorities	Conservation prioritization software Zonation	Conservation planning	Whitehead *et al*. (2014)
Modeling				
Statistical and spatial modeling	Predict mapped features based on quantitative comparison to a set of independent variables	Regression models, SolVES +Maxent application	Ecosystem service assessment, protected area management, urban planning, transport planning	Snizek *et al*. (2013), Samuelsson *et al*. (2018), Sherrouse *et al*. (2011), Sherrouse *et al*. (2014), van Riper *et al*. (2017)
Mathematical modeling	Estimate the local activity space of an individual based on mapped features	Individualized residential exposure estimation model (IREM), fuzzy modeling	Urban planning	Hasanzadeh *et al*. (2018), Hasanzadeh *et al*. (2019)
Sensitivity analysis	Identify uncertainty of a model or a system for outcome	Simulation; sub-sampling; choice of parameters	*Applicable to various domains*	Brown and Pullar (2012), Brown *et al*. (2014b), Hasanzadeh (2019)

5.3.2. Modeling

Regression models have been applied to estimate probabilities of mapped positive and negative experiences in places (Table 3). Snizek *et al*. (2013) applied a logistic multinomial regression model on urban cyclists to estimate the probability of a positive experience versus no experience, and the probability of a negative experience versus no experience, depending on variables such as road environment, cycling facilities, and environmental factors. Using PPGIS survey data on positive and negative experiences in the city of Stockholm, Samuelsson *et al*. (2018) predicted probabilities that if an experience was to occur at the location, it is positive rather than negative, as modeled through spatial logistic regression on environment attributes such as residential or workplace density and closeness to water or major roads.

An open-source statistical modeling application for social value prediction, SolVES (Social Value of Ecosystem Services, http://solves.cr.usgs.gov/), developed by U.S. Geological Survey, quantifies the relationship between density of perceived social values mapped through PPGIS and explanatory environmental variables (e.g. elevation, slope, distance to roads or water) using multiple regression modeling. SolVES was developed in the context of national forest planning (Sherrouse *et al*. 2011). Later, SolVES was integrated with the Maxent maximum entropy modeling software (Elith *et al*. 2010) to generate comprehensive social value maps and to produce robust models (Sherrouse *et al*. 2014, van Riper *et al*. 2017).

PPGIS data have also been used to model people-based environmental exposure in urban context. Hasanzadeh *et al*. (2018) developed an individualized residential exposure model (IREM) to estimate local activity space of an individual, recognizing that the place exposure not only varies from one person to another in its geographical extents, but also from place to place in its magnitude. Mathematical models have also been applied to relate stated residential housing preferences with revealed preferences for the same individuals using empirical data describing the urban structure (Hasanzadeh *et al*. 2019).

Sensitivity analysis refers to a set of methods that can be applied to either the *Explain* or *Predict/Model* phases, to identify the uncertainty of a model or system, typically by varying the inputs and then examining the effects on the outcomes. Sensitivity analysis has not yet achieved widespread use in PPGIS applications but would be useful given the often-inherent limitations in the quantity and/or quality of PPGIS data used as input. For example, varying the quantity of PPGIS data entered in the spatial analysis through simulation or sub-sampling can demonstrate how the quantity of PPGIS data influences the spatial outcomes (Brown and Pullar 2012, Brown *et al*. 2014b) or how the choice of parameters can affect the measurements derived from PPGIS data modeling (Hasanzadeh 2019).

6. Discussion

In this article, we propose a methodological framework to describe and guide method application for data gathered through PPGIS approaches (including PGIS and collecting VGI) to guide both research and practice. The reviewed analysis methods can be grouped in three phases, beginning from *Explore* and advancing to *Explain* and *Predict/Model*, highlighting the depth and breadth of tools and methods applied in spatial PPGIS data analysis. The past decade has witnessed transitions in this field from practical and demonstrative participatory mapping in different planning contexts to a focus on analytical possibilities and challenges associated with PPGIS data aggregation.

Although the cursory analysis, restricted to the *Explore* phase, is often sufficient to support practical management and planning needs, more complex methods have been developed within academia to drive scientific advancements. We encourage a shift towards more evidence-based, or knowledge-informed planning (Rydin 2007, Davoudi 2012) by integrating more complex methods of spatial analysis into the planning process, including elements of exploration, explanation, and prediction. This would entail greater attention to: different sampling strategies for eliciting spatial attributes; different approaches to aggregating spatial attributes (including overlap and conflict analyses); possibilities for integrating different forms of spatial attributes; addressing issues of commensurability and compatibility; and the development of automated analyses tools targeted for practitioners (building on Raymond *et al*. 2014, Brown 2017, Pietilä and Fagerholm 2019, Kenter *et al*. 2019). In addition, an essential future direction relates to determining which methods are most suitable in the context of planning; adapting analyses methods to different phases of planning and decision-making processes (Kahila-Tani *et al*. 2019), each with their different purposes and intended outcomes.

Researchers have an important role in ensuring that the PPGIS data and outputs can be readily applied in planning decisions by advancing methods that account for uncertainty. Identifying data thresholds and confidence intervals is basic to most scientific data, but the current analyses methods for PPGIS data do not estimate the validity of results, thus impeding the greater influence and impact of data and outputs on planning (see, e.g., Brown and Kyttä 2014, Brown and Fagerholm 2015). New analysis methods indicating the level of certainty associated with the spatial PPGIS data and derived results are now required, especially for planning or management decision support (building on the spatial uncertainty classes described by Lechner *et al*. 2014).

Furthermore, as online PPGIS approaches are basically a questionnaires, questions like sampling strategy, sample size, and response rate are critical for interpretation of analytical outputs and also the possible analysis methods. A few important trends need to be highlighted here. First, most countries over the past decades have generally experienced reduced response rates leading to small and possibly biased sample sizes, even in PPGIS surveys (Brown *et al*. 2014a, Brown 2017). Second, partly due to the decreasing response rates, online panels are being increasingly used in PPGIS surveys (e.g. Bijker and Sijtsma 2017). Finally, PPGIS approaches are increasingly being used in citizen science projects to generate big data (Kelling *et al*. 2015, See *et al*. 2016). These trends raise questions about possible analyses on both exceedingly small or very large datasets, and the possible application of data weighting in all phases of PPGIS data analyses.

Along with these, attention needs to be paid to 'what constitutes genuine collaboration in PPGIS studies?', highlighted by Kahila-Tani *et al*. (2019) in their review of over 200 urban and regional planning cases. In the field of public health, this has been addressed successfully in a few 'strongly participatory science' processes. The public not only participated in survey development and data collection, but also in the subsequent data analysis in a form of knowledge justice (Allen 2018). Similarly, Gray *et al*. (2018) highlighted the importance of inclusion of stakeholders and standardized communication about participatory socio-environmental modeling for potential innovation and new insights to collectively reason the environmental problems. In support of the data–information–knowledge–wisdom hierarchy (Rowley 2007), we encourage collected PPGIS data to be made publicly available (following data protection regulations) to make it accessible for analysis and review by the wider public.

Our review indicates that PPGIS data analysis methods are heavily focused on mobilizing knowledge but limited in terms of methods for synthesizing and translating insights across knowledge systems into actionable insights. However, it is a fallacy to assume that more emphasis on analytical methods and tools alone will improve the communicability and usability of PPGIS data. We assert that the coupling of advanced analytical methods with sophisticated knowledge co-creation and deliberative valuation processes, otherwise referred to as pragmatic paradigm including negotiation (Raymond *et al*. 2014), can facilitate communication and uptake of results (Ramirez-Gomez *et al*. 2017, Fagerholm *et al*. 2019b). Analytical methods and co-creation processes need to be developed in tandem to understand how and to what extent individual values articulated in PPGIS surveys become shared and social in collective environmental decision-making processes and how PPGIS approaches can build coalitions for social change (e.g., Kenter *et al*. 2019). Combining analytical tools and processes of knowledge co-creation in this way necessitates a detailed consideration of how issues of conflict, power, and equity are articulated and elicited in PPGIS studies.

PPGIS data analysis methods mostly describe the current state and often overlook the temporal dimension. In particular, there is a lack of methods that would embrace the interrelationships between changes in socio-ecological or urban planning regime/intervention, or changes caused by sudden shocks in systems such as by storms (i.e., place change), and changes in people's place-related values, perceptions, behavior, and preferences (Kendal and Raymond 2018). Longitudinal studies by Brown and Weber (2012) and Brown and Donovan (2014) measured PPGIS values in two surveys with 6 and 14 years in between, respectively, but to cater for the dynamism in global challenges, we need new PPGIS data analysis methods to understanding how people's place-based values form and change at various scales to comprehensively incorporate such dynamics.

The new technological developments offer wide possibilities to extend PPGIS data analysis, for example, to 3D and virtual environments, to elicit indoor values and preferences, or to engage with new forms of geo-navigation. From a visualization perspective, in the field of PPGIS, it is still rare to apply web-based and dynamic tools for visualization (such as open access tools GeoServer (http://geoserver.org/) and OpenLayers (https://openlayers.org/)), which could assist in the creation of potentially effective PPGIS data visualizations. Moreover, the possibilities to harness artificial intelligence, automation, Internet of Things, big data collected through social media, and machine learning to PPGIS data analysis remains unexplored and presents opportunities for new enquiry.

The analysis methods presented here focus on spatial PPGIS data analysis possibilities, but we acknowledge that web-based mapping surveys also yield a rich source of qualitative analysis in terms of the non-spatial PPGIS data. In fact, mixed method approaches are prominently featured in the literature highlighting the advantage of linking participatory mapping, for example, with narrative analysis techniques to elicit landscape values and development preferences (Plieninger *et al*. 2018), social media to share memories of a place (Nummi 2018), or route tracking to monitor mountain bikers (Wolf *et al*. 2018).

7. Conclusions

For data gathered through PPGIS approaches, development of methods has reached a high level of maturity. In this article, we have summarized the depth and breadth of these methods. We provide a framework for scholars interested in PPGIS approaches to guide their thinking, observations, and interpretations. Our framework is based on the categorization of existing methods into three phases, *Explore, Explain, and Predict/Model*, aiming at different depths of understanding and knowledge discovery. We believe the framework is particularly useful for researchers new to the field, to rapidly appraise the different analytical methods available and to guide planning practitioners in using the appropriate techniques to address specific questions or problems.

We urge a renaissance in the field involving: 1) the development of methods considering knowledge-informed planning; 2) the development of easy to understand decision heuristics; 3) PPGIS data analysis in genuine collaboration with the public; 4) coupling analytical methods with deliberative valuation and knowledge co-creation processes, enabling the synthesis and translation of PPGIS insights across knowledge systems into actionable insight; 5) addressing temporal dimensions and dynamics in analysis; and 6) embracing recent technological developments. Considering PPGIS approaches in fields where it has not been applied yet, a more interdisciplinary PPGIS approach would support the emergence of further novel analysis methods. PPGIS approaches provide an operational bridge between social and natural/technical/engineering sciences, thereby offering considerable opportunity to address societal challenges and thus, provide integrated solutions to sustainability problems, as increasingly called for, for example, in terms of biodiversity, nature-based solutions, and climate resilience agendas (Kabisch *et al*. 2017, Diaz *et al*. 2019). This paper provides a solid platform for both understanding existing methods and the development of new methods for addressing such integrated sustainability challenges.

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Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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Notes on contributors

Nora Fagerholm is an Adjunct Professor (Docent) at the Department of Geography and Geology, University of Turku. Her work has focused on applying participatory mapping approaches for assessment of local experiential knowledge on ecosystem services and landscapes in various contexts.

Christopher M. Raymond is a Professor of Sustainability Science at the Helsinki Institute of Sustainability Science, University of Helsinki, Finland. His research is focused on public participation GIS, assessment of the multiple values of nature, senses of place, inclusive conservation, and nature-based solutions.

Anton Stahl Olafsson is an Associate Professor at the section of Landscape Architecture and Planning, Department of Geosciences and Natural Resource Management, University of Copenhagen, Denmark. His research is focused on planning issues related to spatial analyses of people-nature relationships.

Gregory Brown, Professor at California Polytechnic State University, has written multiple seminal works in PPGIS relating to the mapping of place-values to guide natural resource management and regional and urban land-use planning. His work has formed the basis of contemporary research and practice to systematically identify, map, and compare place-values with other landscape inventories.

Tiina Rinne (nee Laatikainen) is a Post-doctoral Researcher at the Department of Built Environment, Aalto University. Her research focuses on health promoting aspects of the built environment, the human-environment interactions primarily from the active living perspective and particularly to the endless possibilities of participatory mapping methods.

Kamyar Hasanzadeh is a Post-doctoral researcher at the Department of Built Environment, Aalto University. His research is mainly focused on geospatial tool development and modeling for environmental health promotion studies.

Anna Broberg is COO and co-founder at Maptionnaire, where she commercializes research results on digital community engagement within the information technology and service industry. Her academic background lies in urban planning, transportation studies, and GIS.

Marketta Kyttä works as a Professor in Land use planning at the Department of Built Environment, Aalto University, Finland. Her work concentrates on research with PPGIS methodology studying themes like environmental health promotion, social sustainability, age- and child-friendly environments and participatory planning.

ORCID

Christopher M. Raymond http://orcid.org/0000-0002-7165-885X
Anton Stahl Olafsson http://orcid.org/0000-0002-7940-8126

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